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Original Article

Optimizing Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration Using Hyper-Node Hamiltonian Relational Quantum Graph Generative Adversarial Attention Networks

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Abstract *- Agriculture is one of the major sources of greenhouse gas (GHG) emissions, and robust prediction models are required to overcome environmental hazards. Conventional techniques remain challenged in the integration of various environmental parameters, thus affecting prediction accuracy. Optimizing Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration Using Hyper-Node Hamiltonian Relational Quantum Graph Generative Adversarial Attention Networks (2HNR-Q2G-N2AN) is a suggested approach by this research to maximize predictive efficiency. The data set GHG emission data contains 5,000 records with 11 environmental factors impacting emissions. Pre-processing is conducted with entropy and τ-Kendall methods, and feature extraction uses the Multi-Axis Vision Transformer (MaxViT) to identify complex dependencies. This is achieved using a new 2HNR-Q2G-N2AN method, which blends Hamiltonian quantum generative adversarial networks (HQuGANs) with a Hyper-node relational graph attention network (HRGATN) and uses the Nutcracker optimizer algorithm (NOA) to optimize its parameters. Experimental results show superb outcomes, achieving a root mean square error (RMSE) that is much lower than current approaches and an accuracy of 99.9%. The proposed approach offers enhanced multi-modal data integration, leading to robust predictions and improved agricultural sustainability.*

Keywords *- Greenhouse gas emissions, Agriculture, Multi-Modal Data Integration, Hamiltonian Quantum Generative Adversarial Networks, Relational Graph Attention Network, Nutcracker Optimizer Algorithm, Entropy preprocessing, τ-Kendall preprocessing, Multi-Axis Vision Transformer.*

1. Introduction

Food and water security, as well as the global climate, depend on the sustainable management of environmental ecosystems. Climate change, extreme weather, and population growth, however, make the effort more difficult. Environmental ecosystem modeling helps with water resource allocation and quality management decision-making by providing information on spatial-temporal dynamics. The spatial-temporal prediction performance of environmental models is enhanced by physical and data-driven models, especially machine learning models. Nevertheless, there are still two major obstacles to overcome: increasing the accuracy of predictions and dealing with the problems brought on by climate change. Because soil respiration raises atmospheric CO2 levels and causes extreme weather, global warming is a problem [1-5]. The biggest developing nation, China, has set lofty goals to reach “carbon neutrality” by 2060 and “peak carbon” by 2030. By 2050, carbon emissions will have increased by 17% if climate change is not addressed. Since soil contributes significantly to atmospheric CO2, precise measurements of soil CO2 fluxes are essential. One major source of atmospheric CO2 and a key output pathway of the soil carbon pool is the soil-derived CO2 flux (SCF). Static chamber, gas chromatography, and micrometeorological flux gradient are examples of conventional ecosystem gas flux measurements. In order to overcome the difficulties of managing missing features and distribution shifts in environmental data, the research suggests the Large Language Model (LLM)-based framework LITE [6-10]. By substituting unique tokens for missing variables, the framework converts spatial-temporal data into semantic time series and temporal trend graphics. It then jointly captures spatial-temporal dynamics and correlations using a vision encoder and a semantic time-series encoder. Information with several granularities is included in the framework and processed in accordance with domain instructions. This novel methodology

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provides continuous robustness to environmental ecosystem distribution variations and varying degrees of missing observations. Straw reflux can assist in lowering Green House Gas (GHG) emissions is challenging to obtain low-cost, high-efficiency, and consistent soil CO2 flux monitoring by employing this method because it is subject to wide field surveys and monitoring throughout the North China Plain wheat growth period, which may be induced by soil warming and straw management. Machine learning is a major tool in addressing research across a number of disciplines due to its ability to form abstract high-level representations through the integration of low-level features in order to search for scattered feature representations of data domains [11-15].

Precisely forecasting Green House Gas (GHG) emissions in agriculture is a daunting task because of the many interdependent factors associated with environmental variables, soil characteristics, climatic parameters, and farming practices. Existing forecasting models are inadequate to grasp the complex interdependencies among these parameters, resulting in inferior forecasting performances. Effective integration of multi-modal data sources, such as satellite images, soil types, and weather data, necessitates sophisticated computational methods to mine significant patterns and relationships. Deep learning models are unable to deal with scalability, interpretability, and computational costs in handling high-dimensional agricultural data. To overcome these issues, this work is motivated.

1.1. Novelty and Contribution

The Novelty and contribution of this paper is given below:

1.1.1. Proposed 2HNR-Q2G-N2AN Model

A novel Hyper-Node Hamiltonian Relational Quantum Graph Generative Adversarial Attention Network that integrates quantum computing principles with graph-based attention mechanisms for enhanced GHG emission prediction.

1.1.2. Multi-Modal Data Integration

Efficiently processes diverse environmental, meteorological, and agricultural datasets using multi-source data fusion to improve predictive accuracy.

1.1.3. Advanced Feature Extraction

Utilizes Multi-Axis Vision Transformer (MaxViT) for high-dimensional feature representation, capturing spatial and temporal dependencies.

1.1.4. Quantum Generative Adversarial Approach

Leverages Hamiltonian Quantum Generative Adversarial Networks (HQuGANs) for better representation learning and uncertainty reduction in predictions.

1.1.5. Graph-Based Attention Mechanism

Incorporates Hyper-Node Relational Graph Attention Network (HRGATN) to model complex dependencies among environmental factors.

1.1.6. Optimization via Nutcracker Algorithm (NOA)

Enhances parameter tuning and network efficiency, reducing RMSE while maintaining high generalization capability.

1.1.7. Real-World Applicability

Supports environmental monitoring, policy-making, and sustainable agricultural practices by providing precise and reliable emission forecasts.

The remaining of this manuscript is organized as Section 2, Literature Review; Section 3, Proposed Methodologies, Section 4, Results and Discussion; Conclusion of Section 5 and Upcoming Projects.

2. Literature Survey

The papers related to the integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods are given below:

In 2024, Li H. et al. [16] introduced a Graph Neural Network (GNN) for the integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods. In order to handle missing features and distribution shifts in environmental data, the study suggests LITE, a multimodal large language model for environmental ecosystem modeling, which reduces prediction error by 41.25%.

In 2024, Yang F. et al. [17] introduced an Auto Former Improvement Network (AFIM) for the integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods. In order to ensure accuracy in short, medium, and long-term projections, a Dish-ECA-Adain-Autoformer combination model was created using data from a self-developed soil respiration monitoring system.

In 2024, Zhao W. et al. [18] introduced an Auto Former Improvement Network (AFIM)for the integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods. With the CatBoost model obtaining the highest accuracy, the study offers a technique for predicting soil nitrogen concentration using satellite imagery and machine learning, improving agricultural management and environmental monitoring.

In 2023, Lee, D. and Choi, Y., et al. [19] introduced a Break for Additive Seasonal Trends (BFAST) method for the integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods. In order to overcome visibility constraints in the Amazon jungle, the paper proposes a learning technique for multi-modal deforestation estimations utilizing satellite footage from Sentinel-1, Sentinel-2, and Landsat 8. Deep neural networks are used in the process, and Attention U-Net performs the best.

In 2023, Fan H. et al. [20] introduced a Landscape Ecological Risk Index (LERI) method for the integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods. Under three scenarios from the sustainable development planning, the study looks at the ecological risk of land use and landscape in Urumqi, Pakistan. The findings indicate that by 2060, the ecological risk of the landscape will have decreased due to the expansion of construction land, woodland and grassland, and unoccupied land.

In 2023 Neethirajan, S., et a1. [21] has introduced an Traditional Phenotyping Methods (TPM) for integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods. The potential of digital phenotyping in broiler genomes is examined in this paper, with particular attention to how it affects sustainability, production resilience, and health monitoring. It also discusses ethical, technical, and integration concerns with digital phenotyping.

In 2023, Neethirajan S. et al. [22] introduced a Generative Adversarial Network (GAN) for the integration of multi-modal data to optimize greenhouse gas emission predictions in agriculture using deep learning methods. The ethical issues of digital cow husbandry involve the potential for inequalities in health and animal welfare outcomes due to the digital divide, calling for prioritization of animal welfare in standards and codes. Table 1 presents an overview of the technique under study.

Table 1. A summary of the approach being assessed

References	Methods	Advantages	Disadvantages
Li, H., et a1. [16]	GNN	Handles missing features and distribution shifts in environmental data. Reduces prediction error by 41.25%, improving greenhouse gas emission modeling.	Computationally costly because of modeling based on graphs. For best results, extensive environmental datasets are needed.
Yang, F., et a1. [17]	AFIM	Uses soil respiration monitoring devices for accurate SCF measurement. Extracts time-series and correlation information effectively.	Physical sensor deployment is necessary, which restricts scalability. It is also susceptible to missing values and data noise.
Zhao, W., et al. [18]	CBM	Combines satellite imagery and machine learning for soil nitrogen prediction. CatBoost model achieves the highest accuracy.	Deep learning predictions have limited interpretability and necessitate excellent satellite image preprocessing.
Lee, D. and Choi, Y. et al. [19]	BFAST	Makes use of multimodal satellite data from Landsat 8, Sentinel 1, and Sentinel 2. In dense trees, Attention U-Net works best, increasing visibility.	Restricted to cloud-affected optical satellite data. Computationally costly in locations with a big scale.
Fan, H., et a1. [20]	LERI	Examines changes in land usage throughout the long future (2020–2060). Assesses scenarios related to sustainability.	Need a great deal of experience with climate modeling. Projections based on scenarios might not always reflect developments in the real world.
Neethirajan, S., et al. [21]	TPM	Uses AI-driven phenotyping to track the health of broilers. Strikes a balance between resilience, productivity, and sustainability.	Implementation presents both technological and ethical difficulties; integration with current farm management systems is necessary.
Neethirajan, S., et al. [22]	GAN	Encourages the use of sustainable livestock-raising methods. Better monitoring of animal welfare is made possible. The topic of AI-powered cattle management is covered.	Raises moral questions about AI taking the place of human monitoring. Issues with the digital divide could lead to disparities in the health of animals.

2.1. Problem Statement

It is a difficult task to precisely forecast Green House Gas (GHG) emissions from agriculture because the environmental factors, soil characteristics, climatic conditions, and agricultural methods have interdependent and multidimensional relationships. The conventional models used for forecasting usually cannot address the complex dependencies between these factors, resulting in less-than-ideal forecasting precision. Combining multi-modal data sources such as satellite images, soil content, and weather conditions necessitates sophisticated computational methods to derive meaningful patterns and relationships. Current deep learning models are challenged with scalability, interpretability, and computational efficiency while handling large agricultural high-dimensional datasets. For this purpose, this work is suggested.

3. Proposed Methodology

In this section, an Optimizing Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration Using Hyper-Node Hamiltonian Relational Quantum Graph Generative Adversarial Attention Networks (2HNR-Q2G-N2AN) to improve predictive performance is proposed. Figure 1 is the workflow diagram that describes 2HNR-Q2G-N2AN. The dataset GHG emission data consists of 5,000 records with 11 features concerning environmental factors affecting emissions. Pre-processing is conducted by applying entropy and τ-Kendall methods, and feature extraction is based on the Multi-Axis Vision Transformer (MaxViT) to identify intricate dependencies. Prediction is achieved through a novel 2HNR-Q2G-N2AN methodology that integrates Hamiltonian Quantum Generative Adversarial Networks (HQuGANs) with a Hyper-node Relational Graph Attention Network (HRGATN), which optimizes parameters through the Nutcracker Optimizer Algorithm (NOA). The suggested method provides improved multi-modal integration of data, resulting in solid predictions and increased agricultural sustainability.

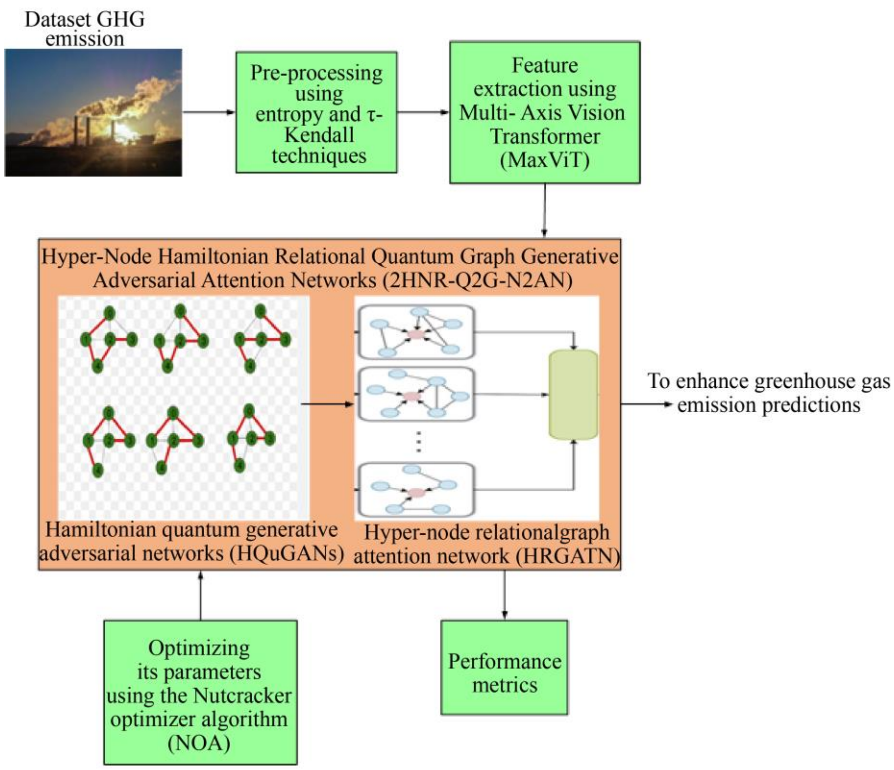


Fig. 1 Workflow diagram of 2HNR-Q2G-N2AN

3.1. Data Acquisition

The input dataset is taken from the titled GHG emission data and contains 5,000 entries with 11 features related to greenhouse gas emissions and environmental factors. It includes Region (North, South, East, West, Central), Temperature (°C) ranging from 5 to 40, Humidity (%) between 10 and 90, Soil pH from 4.5 to 8.5, and Soil Moisture (%) between 5 and 50. The Crop Type feature includes Rice, Wheat, Maize, Soybean, and Cotton. Additional features include Fertilizer Usage (kg/ha) between 50 and 300, Livestock Count (0 to 500), Satellite NDVI (0.2 to 0.9), Satellite Land Surface Temperature (LST) (°C) from 10 to 50, and GHG Emission (CO_2 equivalent) ranging from 50 to 500. Then, these data are given to the entropy and τ-Kendall preprocessing techniques for cleaning the input data, and their explanations are given below:

3.2. Pre-processing Using Entropy and τ-Kendall Preprocessing Techniques

Reliable Green House Gas (GHG) emission forecasts in agriculture necessitate efficient data preprocessing methods to improve data credibility and model stability. The input data has 5,000 instances with 11 features pertaining to GHG emissions and environmental conditions. Pre-processing is conducted with entropy-based feature weighting and τ-Kendall [23] rank correlation, providing the best feature selection and eliminating redundancy in the data.

3.2.1. Entropy Pre-Processing Technique

Entropy, as introduced by Shannon (1948), quantifies the uncertainty and information content of a system. A higher probability of an event leads to lower information gain, whereas a lower probability results in higher information acquisition. Entropy-based feature selection identifies the most relevant attributes influencing GHG emissions by quantifying their information content.

The entropy calculation follows these steps:

Step 1: Normalizing the Decision Matrix

The dataset is first normalized to remove scale disparities between features given in Equation (1):

$$g_{mn} = \frac{y_{mn}}{\sum_{i=1}^{m} y_{mn}}, (i = 1, \ldots, m, j = 1, \ldots, n) \tag{1}$$

Where: y_{mn}represents the original value of the parameter $m$with respect to the attribute$n$, $g_{mn}$is the normalized feature value, $m, n$is the total number of attributes.

Step 2: Calculating Entropy

The entropy $F_m$of each feature is computed using Shannon's entropy formula is given in Equation (2):

$$F_m = -l \sum_{n=1}^{i} g_{mn} \ln g_{mn} \tag{2}$$

where $\ln g_{mn}$is the Entropy constant, n is the Number of parameters and $l$is given in Equation (3):

$$l = \frac{1}{Kmm} \tag{3}$$

Step 3: Determining Uncertainty

The uncertainty for each feature is calculated as Equation (4):

$$c_j = 1 - F_j \tag{4}$$

Wherec_j represents the deviation or importance of the featureF_j.

Step 4: Computing Feature Weights

To determine the relative importance of each feature, weights $\hat{R}_j$are assigned as follows in Equation (5):

$$\hat{R}_j = \frac{b_j}{\sum_{j=1}^{n} b_j} \tag{5}$$

Where $\hat{R}_j$represents the weight vector for the attribute j. Features with higher entropy-derived weights contribute more significantly to the predictive modeling of GHG emissions.

τ-Kendall Pre-Processing Technique

To analyze interdependencies among meteorological and agricultural factors affecting GHG emissions, the τ-Kendall rank correlation is employed. In contrast to Pearson's correlation, which is predicated on data that is regularly distributed, τ-Kendall is a non-parametric approach, making it robust against outliers and non-Gaussian distributions. This is particularly useful for climatological and environmental datasets.

The τ-Kendall coefficient is computed as follows:

Steps to Compute τ-Kendall Correlation:

Rank-Based Pairwise Comparison:

For a dataset consisting of$m$ pairs of observations$(p_1, q_1), (p_2, q_2), \ldots, (p_m, q_m)$, the τ -Kendall correlation coefficient is calculated as in Equation (6):

$$\hat{\rho} = \binom{m}{2}^{-1} \sum_{1<j<i<m} sgn\left[\left(\left(p_j, p_i\right), \left(q_j, q_i\right)\right)\right] \tag{6}$$

Sign Function:

The sign function,$sgn(\Psi)$, is defined as in Equation (7):

$$sgn(\Psi) = \begin{cases} 1 if \Psi > 0 \\ 0 if \Psi = 0 \\ -1 if \Psi < 0 \end{cases} \tag{7}$$

Where $j, i = 1,2, \ldots, n$andΨrepresents the product of differences in the paired observations, τ falls between -1 and +1, with values near -1 denoting a strong negative correlation and values closer to 1 denoting a strong positive correlation.

This preprocessing methodology ensures that redundant features are minimized while preserving the most significant attributes for GHG emission prediction in agricultural environments. The combination of entropy-based weighting and τ-Kendall correlation strengthens the model's robustness, improving prediction accuracy and reducing computational complexity. In order to extract significant characteristics, these data are fed into the feature extraction stage, which is explained below:

3.3. Feature Extraction Using Multi-Axis Vision Transformer (MaxViT) in Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration

Green House Gas (GHG) emission in agriculture is a major contributor to climate change, necessitating the creation of accurate and effective predictive models. Multi-modal data fusion is an important method for improving prediction accuracy through the utilization of heterogeneous datasets such as satellite imagery, weather data, soil attributes, and crop traits. In order to maximize GHG emission predictions, we utilize a new feature extraction mechanism with a Multi-Axis Vision Transformer (MaxViT) [24]. This approach combines the global and local feature representations for improved model performance and generalization.

3.3.1. Multi-Axis Vision Transformer (MaxViT)

Spurred by sparse attention mechanisms, we propose a new feature extraction module; window attention and grid attention are the two sparse forms of fully dense attention processes that are decomposed by Multi-Axis Self-Attention

(Max-SA). The computational complexity is decreased from quadratic to linear by this modification while preserving critical spatial dependencies.

3.4. Attention Mechanism

The self-attention mechanism allows the model to capture spatial correlations between features across different data modalities. Traditional self-attention, as defined in Transformer architectures, operates with quadratic complexity due to full spatial interaction.

3.4.1. Multi-Axis Attention

Multi-axis attention decomposes full attention into local and global interactions by partitioning spatial dimensions:

Block Attention (Local Interactions)

The input feature map $X \in R^{G\times R\times D}$of shape $\left(\frac{H}{P}\times\frac{W}{P}, P\times P, C\right)$is partitioned into non-overlapping windows of size$P\times P$. Self-attention is applied within each local window, enhancing fine-grained feature extraction while maintaining linear computational complexity.

3.5. Grid Attention (Global Interactions)

To address long-range dependencies, we introduce a sparse global attention mechanism using a uniform grid partition$\left(G\times G, \frac{H}{G}\times\frac{W}{G}, C\right)$. This method allows for efficient feature integration across spatially distant regions while maintaining computational feasibility.

3.6. MaxViT Block Architecture

It constructs a hierarchical vision backbone by stacking alternating layers of Max-SA with Mobile Bottleneck Convolution (MBConv). This structure provides a balance between global contextual awareness and locality, essential for agriculture multi-modal data integration.

The Multi-Axis Vision Transformer (MaxViT) is employed for feature extraction in agricultural GHG emission forecasting, improving spatial-temporal analysis, cross-modality learning, and scalability. The novel method exploits local and global interactions to improve model generalization and efficiency.

Then, these data are provided to the Hyper-node Hamiltonian relational quantum graph generative Nutcracker adversarial attention networks (2HNR-Q2G-N2AN) framework improves the Greenhouse Gas Emission Predictions in Agriculture through Multi-Modal Data Integration precisely, and its interpretations are provided below:

3.7. 2HNR-Q2G-N2AN to Enhance Greenhouse Gas Emission Predictions

The Cross Hamiltonian Quantum Contextual Generative Adversarial Hippopotamus Attention Networks (Cross-HQC-GAHAN) framework to improve Greenhouse Gas Emission Predictions. The 2HNR-Q2G-N2AN is a new method for optimizing Greenhouse Gas Emission Predictions in Agriculture through Multi-Modal Data Integration. It utilizes the Cross Hamiltonian Quantum Contextual Generative Adversarial Hippopotamus Attention Networks (Cross-HQC-GAHAN) framework, which combines Hamiltonian Quantum Generative Adversarial Networks (HQuGANs) [25] with a Hyper-Node Relational Graph Attention Network (HRGATN) [26] to improve predictive performance.

The HQuGANs apply quantum-inspired Hamiltonian dynamics to simulate intricate dependencies among agricultural emissions data, supporting effective feature representation for various modalities. The HRGATN, in contrast, represents the relationships among data points as hyper-node relational models, enhancing contextual perception.

The whole model is optimized via the Nutcracker Optimizer Algorithm (NOA) [27], improving parameter tuning and convergence rate and decreasing computational complexity without compromising accuracy. By integrating quantum-inspired generative modeling, state-of-the-art attention mechanisms, and strong optimization, 2HNR-Q2G-N2AN greatly enhances the reliability and scalability of greenhouse gas emission forecasts in agricultural ecosystems and its reasons are as follows:

3.7.1. Hamiltonian Quantum Generative Adversarial Networks (HQuGANs) for Optimizing Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration

To improve Green House Gas (GHG) emission forecasts in agriculture using multi-modal data fusion, we present the Hamiltonian Quantum Generative Adversarial Network (HQuGAN). This model effectively learns unseen quantum states corresponding to intricate agricultural emission behaviors using a quantum-inspired adversarial training procedure. The learning process is founded on a minimax optimization game involving two adversarial quantum players: a generator and a discriminator. Every player uses a Hamiltonian function to optimize corresponding control parameters for precise feature extraction and emissions prediction.

The quantum adversarial game is formulated as follows. At each training iteration, the generator refines its quantum state $\delta(\{e\})$to minimize a cost function$B$, while the discriminator concurrently updates its parameters to maximize by distinguishing between the true quantum state ξ (representing real agricultural emissions data) and the generated state$\delta(\{e\})$.

At every iteration, the generator aims to find an optimal set of control parameters $(\{d\})$such that the generated quantum state $\delta(\{e\})$minimizes the cost function given in Equation (8):

$$A = V \quad (\{d\}) D_0 V(\{c\}) \tag{8}$$

The discriminator optimally selects parameters $c$to maximize$A$, aiming to maximize the distinguishability between $\delta(\{e\})$andξ. This adversarial process continues until a Nash equilibrium is reached, where neither player can improve their strategy independently.

3.7.2. Cost Function Selection and Optimization

The choice of the cost function plays a crucial role in the training dynamics of HQuGAN. Two key cost functions considered are:

Trace Distance Cost Function is given in Equation (9):

$$B = Hg[C(\{c\})(\delta\{e\}) - \xi)] \tag{9}$$

This function minimizes the distance between the generated and true states, ensuring accurate emissions forecasting and Quantum Wasserstein Distance is given in Equation (10):

3.7.3. Quantum Wasserstein Distance

$$C = \left|Hg\left[C(\{c\})\left(\xi - \delta(\{e\})\right)\right]\right|^2 \tag{10}$$

This formulation ensures smooth convergence to the desired state by leveraging optimal transport theory in quantum space.

By iteratively updating ec, the optimization process converges at the Nash equilibrium$(\{e\}^*, \{c\}^*)$, where:

This balance ensures that the resulting state closely approximates the actual emissions data, resulting in strong predictions.

In multi-modal agricultural data fusion, the HQuGAN model is used to distill key emission-related features from diverse datasets (e.g., satellite images, soil composition data, and weather statistics). Encoding these variables into quantum states, HQuGAN effectively captures subtle dependencies, resulting in higher forecasting accuracy. The discriminator ensures the generated emission patterns follow real-world agricultural emissions patterns, maximizing predictive robustness.

Through the application of the quantum-inspired adversarial training process, HQuGAN improves the accuracy, scalability, and interpretability of GHG emission forecasts, making it a useful tool for sustainable agricultural planning and climate footprint estimation.

Then, for enhancing the performance of the Hamiltonian Quantum Generative Adversarial Network (HQuGAN) with Hyper-node relational graph attention network (HRGATN) for Optimizing Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration, the following are given below:

Hyper-node Relational Graph Attention Network for Optimizing Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration

Green House Gas (GHG) emissions play a critical role in climate change; thus, prediction is very important for sustainable agricultural production. Multi-modal data sources improve the accuracy of emission estimation.

This work introduces a novel Hamiltonian Quantum Generative Adversarial Network (HQuGAN) along with a Hyper-node Relational Graph Attention Network (HRGATN) to improve GHG emission predictions through an efficient combination of multi-modal data representations.

Multi-Modal Data Fusion Using Low-Rank Tensor Representation

Multi-modal fusion enables entities to leverage complementary information present in different sources of agricultural data, such as satellite imagery, soil composition, weather patterns, and farming practices.

Traditional multi-modal knowledge graph embedding methods utilize concatenation or attention mechanisms; however, they often overlook intra-modality and inter-modality dynamics. Tensor fusion is an effective approach, transforming input representations into high-dimensional tensors before mapping them to lower-dimensional feature vectors.

The display of hyper-nodes g created using tensor fusion is calculated as Equation (11):

$$g = e(R; F, m) = F \cdot R + m, (g, m \in \Re^{c_h}) \tag{11}$$

Where F is the weight and m is the bias, $R = \otimes_{p=1}^{P} u_p \mathrm{Z}$ is the tensor outer product that creates the high-dimensional tensor$\otimes$ Across a collection of vectors representing unimodal representations with 1 appended as$g_p = \{(g^t, 1), (g^u, 1), (g^b, 1)\}$, and m means the pth modal.

Information Aggregation Using Hyper-node Relational Graph Attention Network

Graph Neural Networks (GNNs) leverage graph structures to propagate information across interconnected entities, refining entity representations. HRGATN employs a relational graph attention mechanism to aggregate hyper-node information from neighboring nodes, capturing structural dependencies.

Relation-Specific Attention Mechanism

To measure the importance of neighboring nodes, relation-specific attention is introduced in Equation (12):

$$R = \begin{bmatrix} g^s \\ 1 \end{bmatrix} \otimes \begin{bmatrix} g^u \\ 1 \end{bmatrix} \otimes \begin{bmatrix} g^b \\ 1 \end{bmatrix} = (g^t, g^u, g^b) + (g^t \otimes g^u, g^t \otimes g^b g^u \otimes g^b) + g^t \otimes g^u \otimes g^b. \quad (12)$$

In multi-modal tensor fusion, the first three subregions gain from the tensor outer product. g^t, g^u and g^b are uni-modal embeddings, which are able to capture the intra-modality of every single modal piece of information. Next, the subsequent three subregions $g^t \otimes, g^t \otimes g^b g^u \otimes g^b$ in represent bi-modal interactions, and the last $g^t \otimes g^u \otimes g^b$ represent Tri-modal interactions that are capable of capturing the intermodality in multi-modal information tensor fusion.

3.7.4. Relational Aggregation Function

Inspired by spatial convolutions in GCNs, the hyper-node representation is iteratively refined by aggregating information from neighboring nodes:

First, we employ weight decomposition with low rank $\hat{F}$ as a substitute for the weight tensor F is given in Equation (13):

$$\hat{F} = \sum_{a=1}^{l} \bigotimes_{P}^{p=1} w_p^{(a)} \quad (13)$$

The minimal l rank of the tensor is what gives the decomposition its validity. The vector sets $w_p^{(a)}$ are referred to as the original weight tensor's decomposition factors, where m is p -th modal, and i means the a^{th} decomposition factor. Hence, Equation (13) can be converted to (bias k is omitted here):

Prediction

HQuGAN enhances emission predictions by leveraging quantum computing principles for generative modeling. It employs a quantum Hamiltonian evolution operator to encode data distributions and adversarially train a generator and discriminator.

Three modalities' low-rank multimodal fusion representation, e, can be written as Equation (14):

$$g = \left(\sum_{a=1}^{l} w_s^{(a)} \cdot g_s\right) \circ \left(\sum_{a=1}^{l} w_u^{(a)} \cdot g_u\right) \circ \left(\sum_{a=1}^{l} w_b^{(a)} \cdot g_b\right) \quad (14)$$

Using Equation (14), compute g without the burden of calculating the enormous input tensor straight from the input pre-trained embeddings and their modal-specific decomposition components F and R. In the meanwhile, Equation (14) makes it simple to express a variety of modalities (for example, two modalities can be represented by two product terms in Equation (14)). Finally, the completely differentiable processes that make up low-rank multi-modal fusion allow the parameters to $\left\{w_p^{(a)}\right\}_{a=1}^{l}$ must be acquired through back-propagation from beginning to conclusion.

This study integrates HRGATN with HQuGAN to optimize greenhouse gas emission predictions in agriculture through multi-modal data fusion. The HRGATN efficiently aggregates relational dependencies in multi-modal knowledge graphs, while HQuGAN enhances the generative modeling of agricultural emissions. Future work will extend the approach to real-time emission monitoring with quantum-enhanced Bayesian inference.

Then HQuGANs-HRGATN weight parameters are tuned to lower the error rate, cost, and processing complexity through Nutcracker Optimizer Algorithm (NOA) to Optimize Green House Gas Emission Predictions in Agriculture via Multi-Modal Data Integration and its explanations are as follows:

Nutcracker Optimizer Algorithm (NOA) for optimizing weight parameters of HQuGANs-HRGATN to Optimize Greenhouse Gas Emission Predictions in Agriculture via Multi-Modal Data Integration

The Nutcracker Optimizer Algorithm (NOA) is employed to optimize the weight and bias parameters of the Hamiltonian Quantum Generative Adversarial Network (HQuGAN) integrated with the Hyper-node Relational Graph Attention Network (HRGATN). The objective is to improve the predictive performance, computational speed, and general robustness of greenhouse gas emission forecasts in agriculture based on multi-modal data integration. NOA mimics nutcrackers' foraging and caching behavior, allowing for an optimal balance between exploration and exploitation. Figure 2 shows the Flowchart of 2HNR-Q2G-N2AN.

Step 1: Initialization of Candidate Solutions

A population of candidate solutions is randomly initialized, with each one representing distinct hyperparameter values for the HQuGANs-HRGATN model. The candidates are scattered in a specified search space to provide diversity and prevent premature convergence. The initial solutions are evaluated based on the following factors:

Prediction Accuracy (PA)

The model's ability to accurately predict greenhouse gas emissions.

Computational Efficiency (CE)

The capacity to process large-scale multi-modal data efficiently.

Model Complexity (MC)

The balance between computational resources and performance.

Step 2: Exploration Phase via Random Perturbation

To enhance global search capabilities, small random perturbations are applied to candidate solutions. This mechanism prevents the optimizer from getting stuck in local optima and ensures better exploration of the search space.

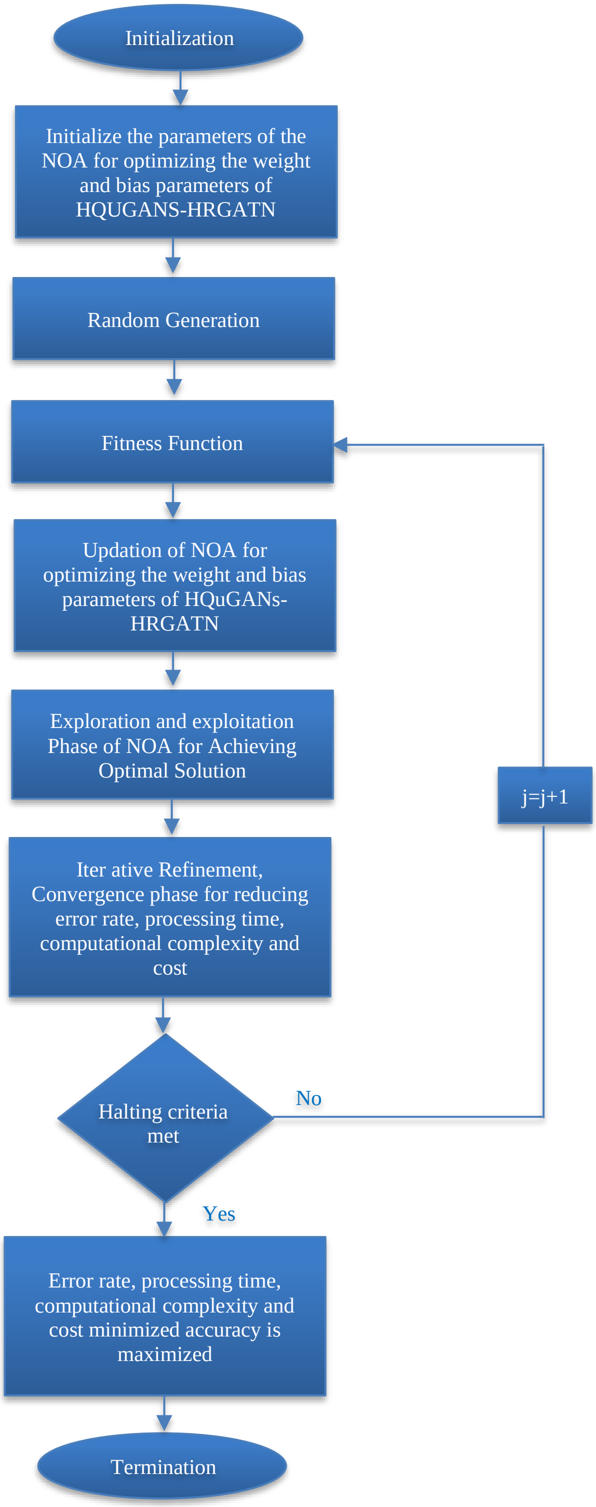


Fig. 2 Flowchart of 2HNR-Q2G-N2AN

Step 3: Fitness Function Evaluation

The fitness function evaluates the candidate solutions based on prediction accuracy, computational efficiency, and model complexity. The fitness function is mathematically defined as in Equation in (15):

$$Fitness function = Optimize(\beta) \tag{15}$$

The objective is to minimize while increasing classification accuracy in order to maximize computational efficiency and model complexity.

Step 4: NOA update to maximize the weight and bias parameters of HQuGANs-HRGATN

The weight and bias parameters of HQuGANs-HRGATN are iteratively updated using NOA. In this phase, the algorithm exploits promising solutions $\vec{X}^s_{m,n}$ by refining their positions based on the best candidate given in Equation (16):

$$\vec{X}^s_{m,n} = \left(\overrightarrow{u_n} - \overrightarrow{L_n}\right).\overrightarrow{WY} + \overrightarrow{K_n}, m = 1,2,\dots,M, n = 1,2,\dots,D \tag{16}$$

Where $\overrightarrow{u_n}$ and L_n are the randomly selected solutions from the population. $\overrightarrow{K_n}, m, \overrightarrow{WY}$, $m = 1,2,\dots,M, n = 1,2,\dots,D$ are the Parameters controlling the balance between exploitation and diversification.

This ensures that the model converges toward an optimal configuration with minimized computational cost and improved prediction accuracy.

Step 5: Iterative Optimization and Termination Criteria

The optimization process iterates through exploration and exploitation cycles until one of the following termination conditions is met:

Maximum Iterations

The algorithm halts after a predefined number of iterations.

Convergence

If the fitness function shows negligible improvement over consecutive iterations.

Nutcracker Optimizer can efficiently optimize the weight parameters of HQuGANs-HRGATN and lower computational complexity, cost, and error rate by optimizing greenhouse gas emission predictions in agriculture using multi-modal data integration.

It can improve prediction accuracy and robustness using graph-based deep learning models combined with quantum adversarial optimization methods.

This research maximizes greenhouse gas emission forecasting in agriculture with 2HNR-Q2G-N2AN, coupling Hamiltonian Quantum Generative Adversarial Networks (HQuGANs) with a Hyper-node Relational Graph Attention Network (HRGATN). It handles 5,000 inputs through entropy and τ-Kendall methods, performs feature extraction with MaxViT, and parameter optimization with the Nutcracker Optimizer Algorithm (NOA) for advanced multi-modal data coupling and sustainability. The next section then provides a performance analysis.

4. Results and Discussions

In this section, the Results and Discussions of Hyper-Node Hamiltonian Relational Quantum Graph Generative Adversarial Attention Networks (2HNR-Q2G-N2AN) for Greenhouse Gas Emission Predictions are discussed.

4.1. Dataset Description

The input dataset is taken from the titled GHG emission data and contains 5,000 entries with 11 features related to greenhouse gas emissions and environmental factors. It includes Region (North, South, East, West, Central), Temperature (°C) ranging from 5 to 40, Humidity (%) between 10 and 90, Soil pH from 4.5 to 8.5, and Soil Moisture (%) between 5 and 50. The Crop Type feature includes Rice, Wheat, Maize, Soybean, and Cotton. Additional features include Fertilizer Usage (kg/ha) between 50 and 300, Livestock Count (0 to 500), Satellite NDVI (0.2 to 0.9), Satellite Land Surface Temperature (LST) (°C) from 10 to 50, and GHG Emission (CO_2 equivalent) ranging from 50 to 500. Of them, 20% are used for testing, and 80% are used for teaching. Table 2 lists the precise parameters that were used for the implementation.

Table 2. Implementation Parameters

Parameters	Description
Proposed Neural Network	2HNR-Q2G-N2AN
OS	Windows 10
Optimization	NOA
Dataset	GHG emission Dataset
Software	Python 3.7

4.2. Performance Metrics

The suggested 2HNR-Q2G-N2AN method's performance is contrasted with that of the current approaches, including GNN [16], AFIM [17], CBM [18], BFAST [19], LERI [20], TPM [21], and GAN [22], respectively, employing performance criteria like mistake rate, recall, f1 score, accuracy, precision, Train time, computational complexity, processing time, Hamming loss, Mean Squared Error (MSE), mean absolute error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) analysis.

Table 3 provides the equations for the performance.

Metrics:

Table 3. Performance metrics

Performance metrics	Equations (17-22)
Precision	$\frac{1}{L}\sum_{l=1}^{F}\left(\frac{\lvert Xy(a_l)\cap s_l\rvert}{\lvert Xy(s_l)\rvert}\right)$ (17)
Recall	$\frac{1}{L}\sum_{l=1}^{F}\left(\frac{\lvert Xy(a_l)\cap s_l\rvert}{\lvert s_l\rvert}\right)$ (18)
F1-Score	$\frac{1}{L}\sum_{l=1}^{F}\left(\frac{2\lvert Xy(a_l)\cap s_l\rvert}{\lvert Xy(s_l)\rvert+\lvert s_l\rvert}\right)$ (19)
Accuracy	$\frac{1}{L}\sum_{l=1}^{F}\left(\frac{\lvert Xy(a_l)\cap s_l\rvert}{\lvert Xy(a_l)\cup s_l\rvert}\right)$ (20)
MAE	$\frac{1}{L}\sum_{(r,s)}\lvert\hat{f}_{a,x}-f_{a,x}\rvert$ (21)
RMSE	$\sqrt{\frac{1}{L}\sum_{(r,s)}(\hat{f}_{a,x}-f_{a,x})}^{2}$ (22)

Where, a_l described as the input of a classification method, s_l described as the result of the categorization procedure, Lis the dataset's total number of instances, Xy is the method of training, Xy(a_l) and is shown as the output labels that the classification technique predicts. f_(a,x) is the user's actual rating r for the items. f^_(a,x) is the one that was anticipated.

4.3. Performance Analysis

The performance analysis of 2HNR-Q2G-N2AN is discussed here:

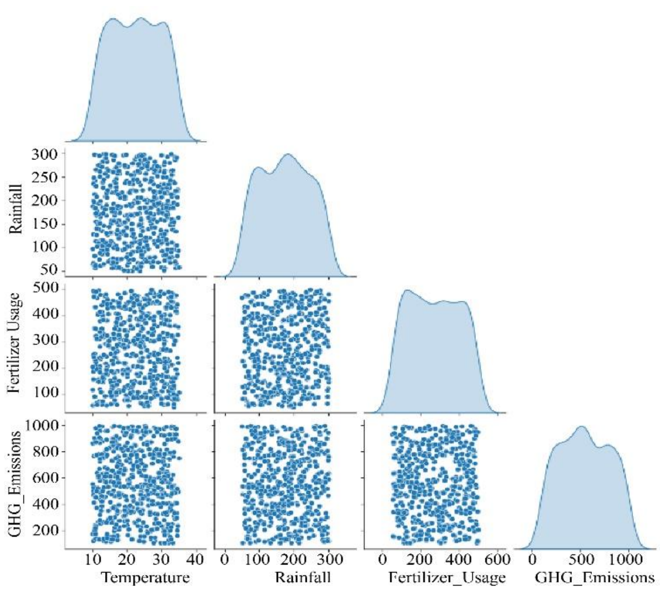


Fig. 3 Numerical feature

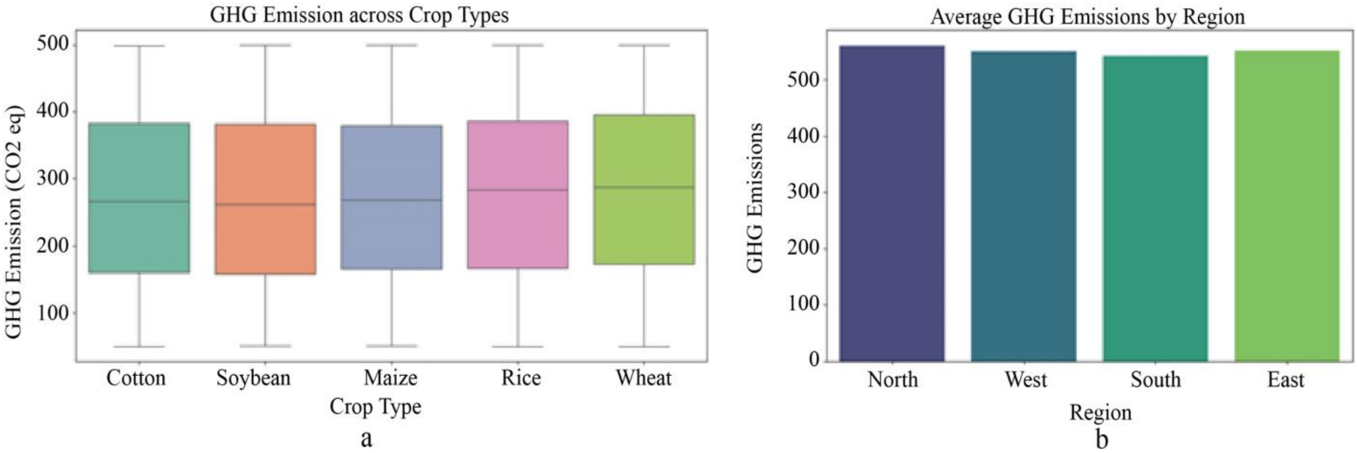


Fig. 4 (a) GHG emission across crop types for cotton, soybean, maize, rice, and wheat (b) average GHG emissions by region for north, west, south, and east

Figure 3 shows the numerical features. Temperature, Rainfall, Fertilizer_Use, and GHG_Emissions are the numerical features that are represented in the image as a pair plot. Distributions are indicated by the diagonal, which displays Kernel Density Estimates (KDE) for every variable. Potential correlations can be seen in the paired associations displayed by the scatter plots in the lower triangle. Since the points seem well-spaced, there may not be any significant relationships. "Pair plot of Numerical Features," the title, encapsulates the goal. Finding trends and connections between variables is one way that this visualization aids in exploratory data analysis.

Figure 4 shows the (a) GHG emission across crop types for cotton, soybean, maize, rice, and wheat and (b) average GHG emissions by region for north, west, south, and east. Due to variations in agricultural methods, soil composition, and resource use, greenhouse gas emissions can fluctuate between crop varieties and geographical areas. The emission levels of cotton, soybean, maize, rice, and wheat vary according to irrigation, fertilizer application, and rates of decomposition. Additionally, climate, soil fertility, and agricultural intensity all affect the regional averages (North, West, South, and East). In order to reduce the influence on the environment, it is helpful to focus on emission reduction initiatives, optimize farming practices, and implement sustainable agriculture regulations.

Figure 5 shows the (a) temperature vs. GHG emissions and (b) correlation matrix for GHG emissions Fertilizer usage, rainfall, and temperature. Higher temperatures have an impact on GHG emissions because they can speed up soil microbial activity. This relationship can be seen in a scatter plot of temperature versus greenhouse gas emissions. Furthermore, a correlation matrix measures the correlations between temperature, rainfall, fertilizer use, and greenhouse gas emissions. Potential dependencies, such as higher emissions due to increased fertilizer use, are indicated by strong correlations. Planning for sustainable agriculture benefits from an understanding of these relationships since it reduces emissions and maximizes resource usage for better economic and environmental results.

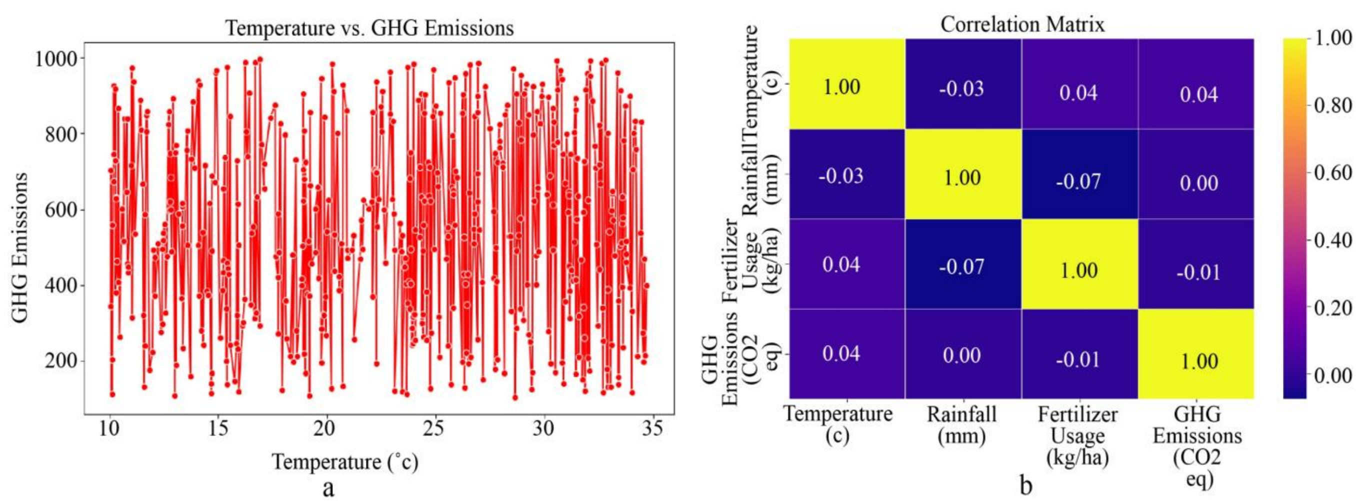


Fig. 5 (a) temperature vs. GHG emissions and (b) correlation matrix for GHG emissions Fertilizer usage, rainfall and temperature

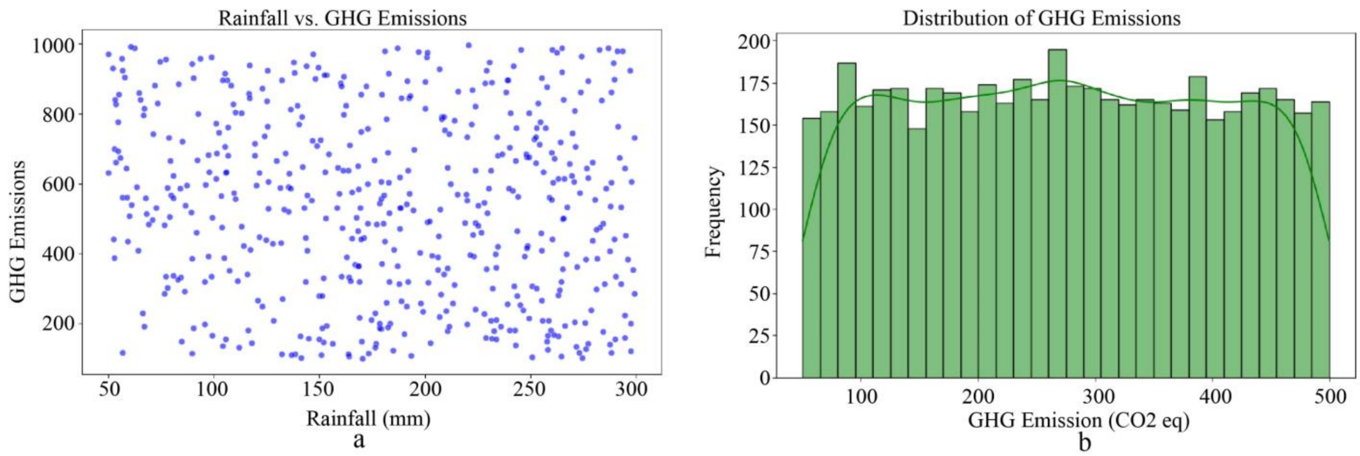


Fig. 6 (a) rainfall vs. GHG emissions and (b) distribution of GHG emission

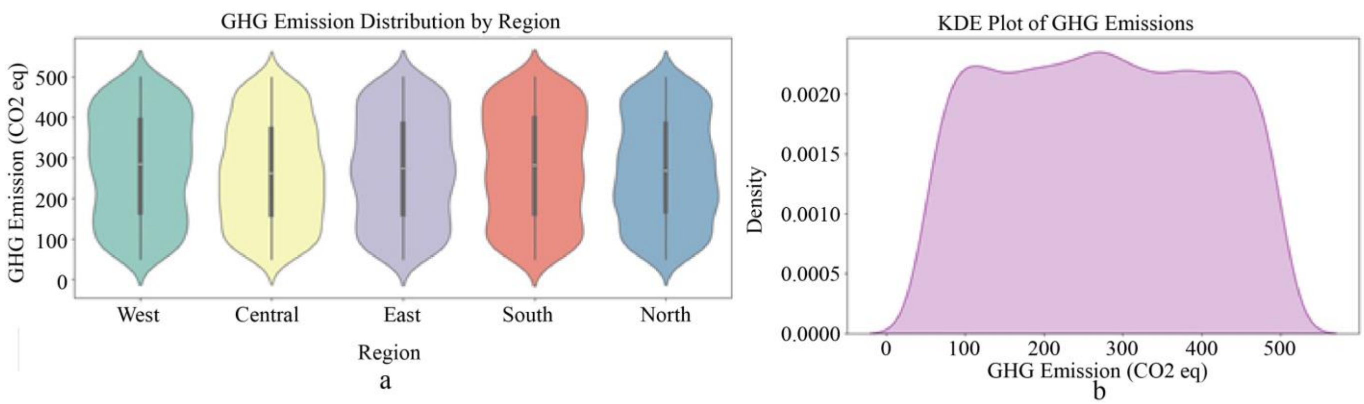


Fig. 7 (a) GHG emission distribution by region and (b) KDE plot of GHG emissions

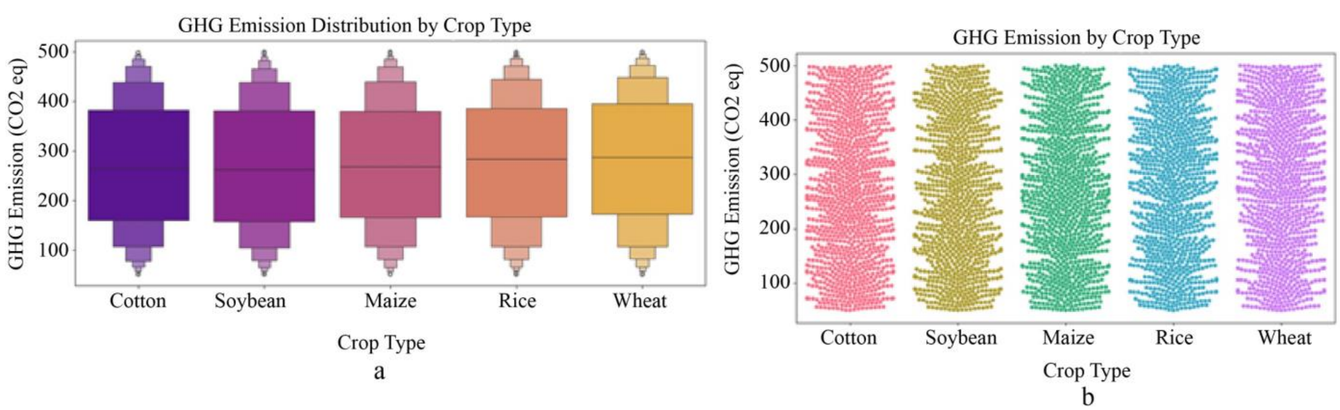


Fig. 8 (a) GHG emission distribution by crop type and (b) swarm plot GHG emission by crop type

Figure 6 shows the (a) rainfall vs. GHG emissions and (b) distribution of GHG emissions. Rainfall influences fertilizer runoff, microbial activity, and soil moisture, all of which have an impact on GHG emissions. Trends, such as increased emissions in locations that are prone to flooding or drought, can be discovered using a scatter plot of rainfall vs greenhouse gas emissions. Furthermore, a histogram or density map that displays the distribution of GHG emissions shows emission patterns, peaks, and fluctuations. By optimizing water management and lowering emissions for more sustainable farming methods, an understanding of these linkages supports climate-smart agriculture.

Figure 7 shows the (a) GHG emission distribution by region and (b) KDE plot of GHG emissions. Because of variations in temperature, soil, and farming methods, GHG emissions range by area. Finding high-emission regions and comparing emission levels are made easier with the use of a distribution plot by region (North, West, South, and East). Furthermore, a smoothed representation of the total emission distribution that highlights peaks and variability is offered by a Kernel Density Estimate (KDE) plot of GHG emissions. These insights support the implementation of region-specific policies for sustainable farming and environmental conservation, the targeting of emission reduction initiatives, and the optimization of agricultural practices.

Figure 8 shows the (a) GHG emission distribution by crop type and (b) swarm plot of GHG emission by crop type. Different crop kinds have different GHG emissions because of variations in irrigation, fertilizer use, and rates of decomposition. Emission trends and variances are displayed in a distribution plot of GHG emissions by crop type (such as cotton, soybean, maize, rice, and wheat). Furthermore, a swarm plot illustrates the density and distribution of emissions for every crop type by visualizing individual data points. In order to promote climate-friendly agriculture, these assessments aid in identifying high-emission crops, directing sustainable farming methods, maximizing resource utilization, and creating focused emission reduction plans.

Figure 9 shows the (a) GHG emission by crop type and (b) GHG emissions distribution by region. Due to variations in agricultural methods, soil composition, and resource utilization, greenhouse gas emissions differ by crop variety and geographical location. The crops that contribute most to emissions are shown in a bar plot of GHG emissions by crop type (e.g., cotton, soybean, maize, rice, and wheat). Furthermore, regional variations driven by climate and agricultural intensity are displayed in a distribution plot by region (North, West, South, and East). By lowering emissions while preserving environmental balance and production, these insights promote sustainable farming practices.

Figure 10 shows the (a) GHG emissions vs. fertilizer usage and (b) 3D Convergence plot. Because too much fertilizer raises nitrous oxide emissions, there is a strong correlation between GHG emissions and fertilizer use. Trends, such as increasing emissions with increased fertilizer use, can be found using a scatter plot of GHG Emissions vs. Fertilizer Usage. Furthermore, a 3D convergence graphic illustrates how several variables, including temperature, precipitation, and fertilizer use, interact with greenhouse gas emissions. For increased productivity and decreased emissions, these insights aid in the development of sustainable agriculture practices, fertilizer application optimization, and environmental impact reduction.

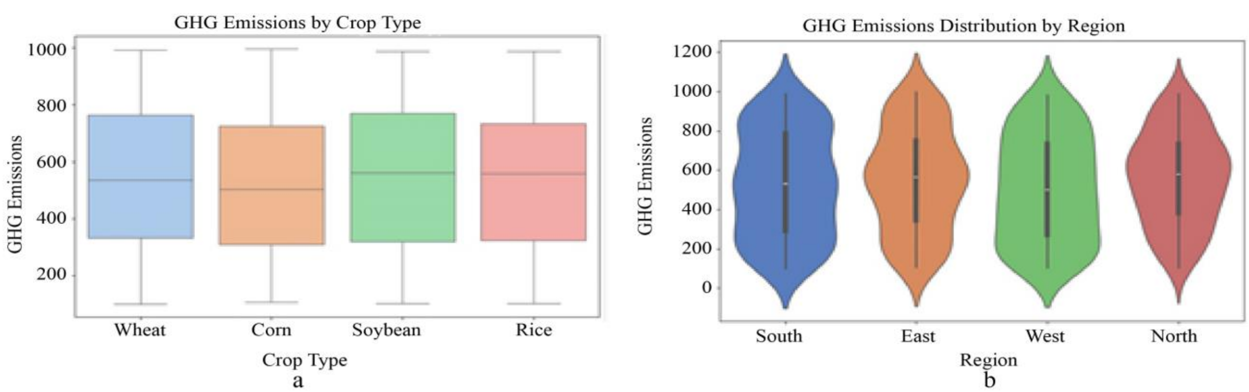


Fig. 9 (a) GHG emission by crop type and (b) GHG emissions distribution by region

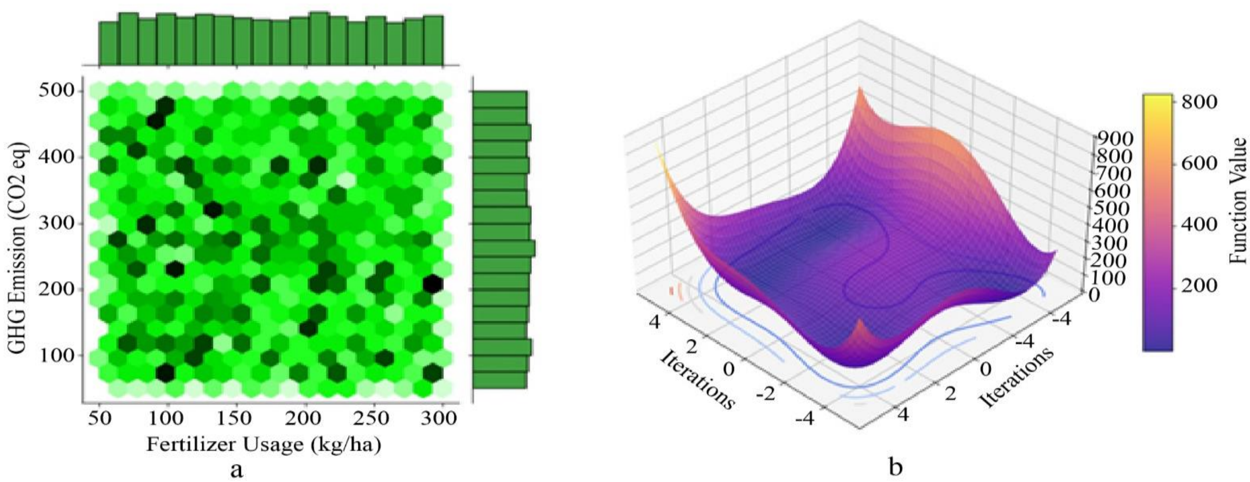


Fig. 10 (a) GHG emissions vs. fertilizer usage and (b) 3D Convergence plot

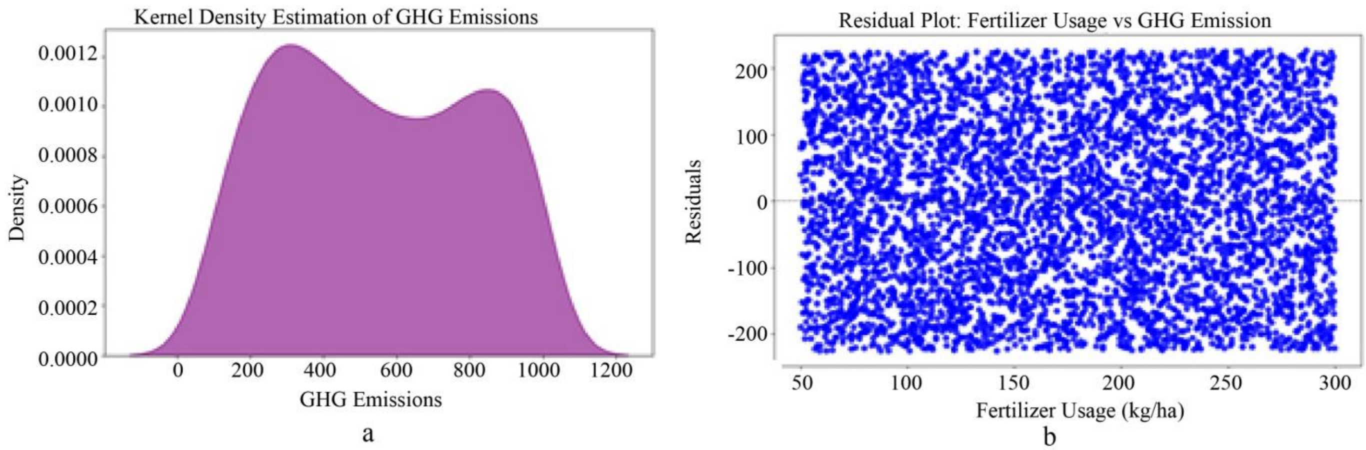


Fig. 11 (a) kernel density estimation of GHG emissions and (b) residual plot: fertilizer usage vs GHG emission

Figure 11 shows the (a) kernel density estimation of GHG emissions and (b) residual plot: fertilizer usage vs GHG emission. Peaks and variations in emission levels across data points are highlighted in a smoothed distribution of GHG emissions produced by a Kernel Density Estimation (KDE) plot. Additionally, by displaying the variations between expected and actual values, a residual plot for Fertilizer Usage vs. GHG Emissions evaluates the model fit. Patterns in the residuals show whether emissions are influenced by nonlinear processes or if a linear model is adequate. When combined, these evaluations aid in the development of sustainable methods to reduce greenhouse gas emissions, the optimization of fertilizer use, and the enhancement of prediction models.

Figure 12 shows the Pair plot of Environmental Factors and GHG Emissions across Crop Types. For various crop kinds (Cotton, Soybean, Maize, Rice, and Wheat), the pairplot illustrates the correlations between temperature, humidity, soil pH, and greenhouse gas emissions. The distribution of each feature's Kernel Density Estimates (KDE) is displayed on the diagonal. Using colors to identify crops, scatter plots compare variables. Weak associations between components are suggested by the dense scatter. Sustainable farming methods and emission reduction plans benefit from this visualization's analysis of the relationship between environmental factors and GHG emissions.

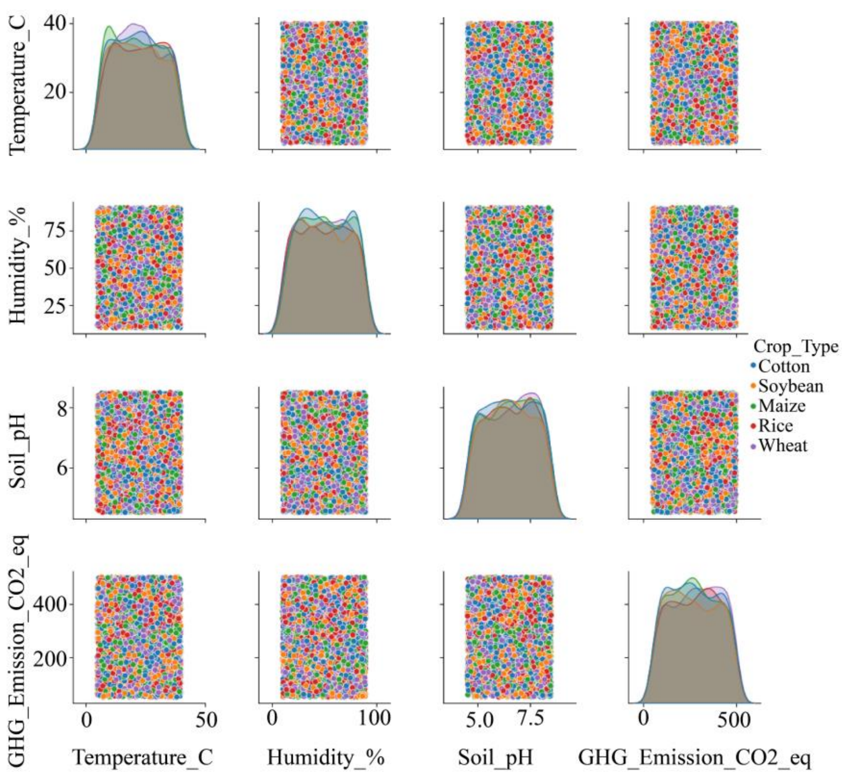


Fig. 12 Pair plot of Environmental Factors and GHG Emissions across Crop Types

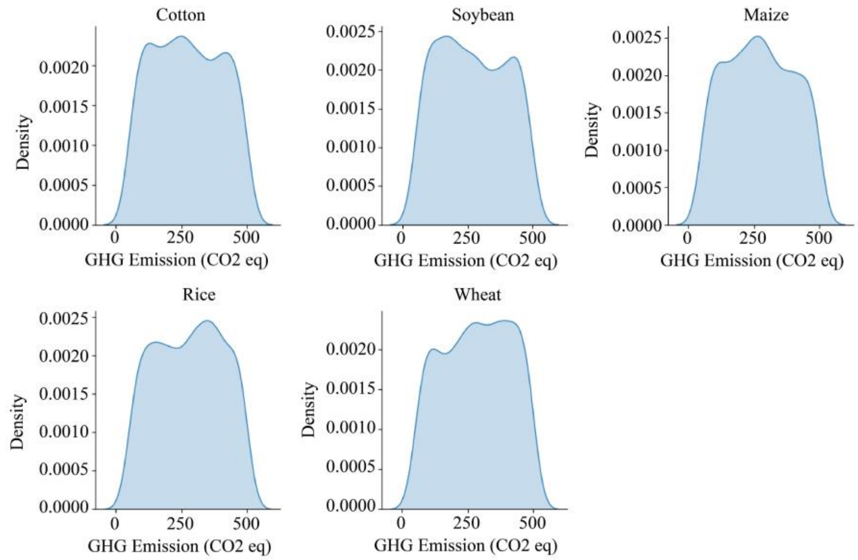


Fig. 13 Kernel Density Estimation of GHG Emissions by Crop Type

Figure 13 shows the Kernel Density Estimation of GHG Emissions by Crop Type. The graphic shows the distribution of greenhouse gas emissions (CO2 equivalent) for the following crops: wheat, rice, corn, soybeans, and cotton. The distribution of emissions is displayed by each Kernel Density Estimation (KDE) curve, emphasizing variability and peaks. Crops exhibit slightly different emission patterns, with some displaying bimodal distributions. In order to encourage sustainable agriculture practices that aim to lessen the environmental impact while preserving productivity, this research assists in identifying which crops contribute more to emissions.

Figure 14 shows the count of crop types for rice, corn, soybean, and wheat. In agricultural datasets, the number of crop types, rice, corn, soybeans, and wheat, helps examine how they are distributed. An understanding of cropping patterns can be gained by visualizing the frequency of each crop using a bar plot or frequency table. Dominant crops are indicated by higher counts, which may be related to demand, farming methods, or climate suitability. Planning for sustainability, policymaking, and resource allocation are all aided by an understanding of these distributions. According to this research, effective land use maximizes yield while reducing negative environmental effects like greenhouse gas emissions.

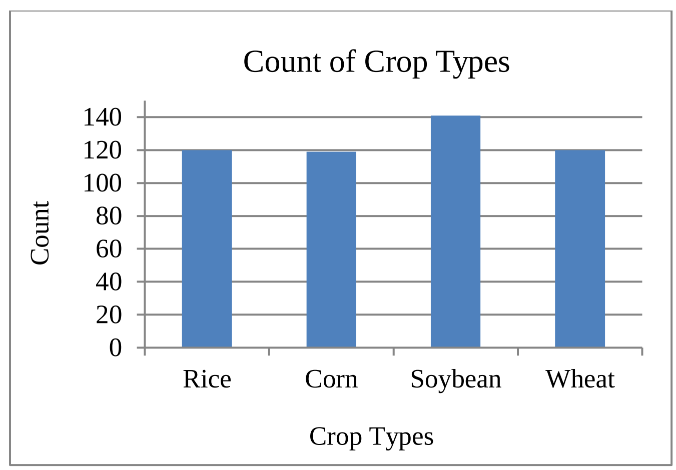
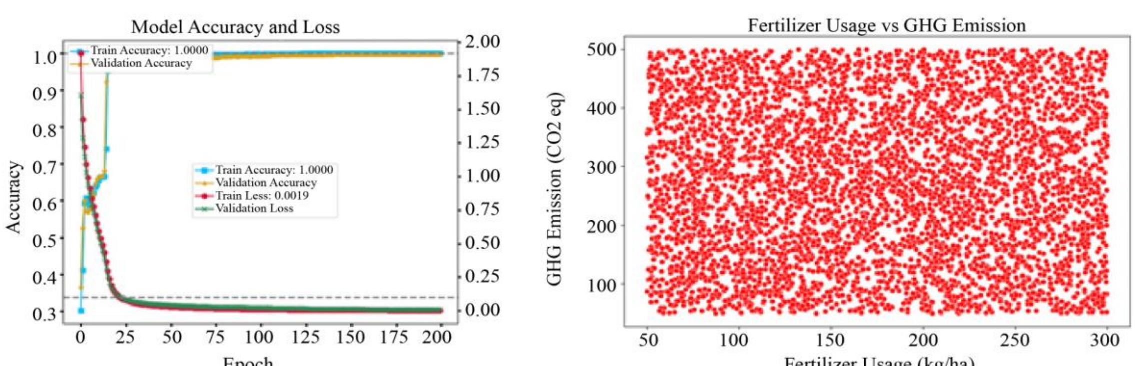


Fig. 14 Count of crop types for rice, corn, soybean, and wheat



a

b

Fig. 15 (a) model accuracy and loss for epoch and (b) fertilizer usage vs GHG emission

Figure 15 shows the (a) model accuracy and loss for epoch and (b) fertilizer usage vs GHG emission. A machine learning model's performance is gauged by its accuracy and loss over time. While loss measures errors, accuracy indicates how well forecasts match real values. Plotting accuracy and loss across epochs facilitates the evaluation of overfitting and convergence. Furthermore, a comparison between fertilizer usage and greenhouse gas emissions shows that excessive fertilizer use raises emissions. Sustainable farming methods might be guided by trends that are highlighted by a scatter plot. In order to lessen the influence on the environment, combining this knowledge helps to improve predictive models and create environmentally friendly farming practices.

Table 4 shows the overall performance of the suggested approach in contrast to existing methods. The table contrasts several models based on performance indicators. The 2HNR-Q2G-N2AN (Proposed) model outperforms other models, such as BFAST (95.23%) and GNN (78.90%), achieving the maximum accuracy (99.98%). Its balanced performance is demonstrated by its great recall (97.58%), precision (95.45%), and specificity (98.33%). Its RMSE (6.2) and MSE (8.5) indicate some prediction mistakes, though. Its AAE (2.1) is the lowest in spite of this, indicating excellent predictive stability. The outcomes validate the model's efficacy in contrast to conventional methods.

Table 5 shows the evaluation of the proposed method in comparison to existing methods using statistics. The table contrasts the Variance Inflation Factor (VIF), mean, standard deviation, and statistical test p-values for several approaches, including the suggested 2HNR-Q2G-N2AN model. Significant differences from alternative models are indicated by lower p-values for the suggested model across several tests. Its high standard deviation (4,892.38) and mean (62,829.50) indicate variability, yet its low VIF (1.001) suggests little multicollinearity. The outcomes demonstrate how effective it is in comparison to other models, such as GNN, AFIM, and GAN, making it a viable strategy in the particular situation.

Table 4. Overall performance of the suggested approach in contrast to existing methods

Metrics	GNN [16]	AFIM [17]	CBM [18]	BFAST [19]	LERI [20]	TPM [21]	GAN [22]	2HNR-Q2G-N2AN (Proposed)
Accuracy	78.90	90.57	91.45	95.23	92.77	93.24	90.10	99.98
Recall	98.22	91.35	89.28	97.59	97.80	92.34	89.12	97.58
Precision	94.46	95.35	79.27	90.37	94.66	95.99	89.23	95.45
Specificity	78.90	90.57	91.45	95.23	91.29	98.24	84.44	98.33
F1-Score	79.90	91.56	89.45	95.28	93.34	96.46	93.89	94.20
MSE	5.6	4.4	7.6	2.5	7.7	3.5	5.7	8.5
MAE	6.1	7.3	3.5	4.7	1.9	2.0	5.2	5.4
RMSE	7.2	3.4	6.6	7.8	2.7	2.2	5.4	6.2
AAE	8.7	5.3	6.5	7.6	8.4	4.2	3.2	2.1

Table 5. Comparison of the suggested approach with current approaches using statistics

Methods	SW Test p-Value	WSR test / U-test p-Value	H-test p-Value	KS test p-Value	FT p-Value	Mean	Standard Deviation	Variance Inflation Factor
GNN [16]	0.456	0.26	0.243	0.034	0.082	47,784.8	1863.45	1.87
AFIM [17]	0.371	0.67	0.186	0.019	0.065	63,085.55	1357.32	1.25
CBM [18]	0.774	0.89	0.679	0.057	0.043	40,538.14	2631.60	1.44
BFAST [19]	0.232	0.94	0.726	0.014	0.072	33,187.10	1654.54	1.62
LERI [20]	0.763	0.32	0.896	0.088	0.092	64,563.45	1864.33	1.32
TPM [21]	0.195	0.69	0.965	0.056	0.064	47,123.80	4876.27	1.87
GAN [22]	0.854	0.22	0.643	0.067	0.082	59,28113	2823.82	2.78
2HNR-Q2G-N2AN (Proposed)	<0.001	<0.001	<0.001	<0.001	<0.001	62,829.50	4,892.38	1.001

Table 6. Ablation study

Model Configuration	HQuGANs	HRGATN	Nutcracker optimizer	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Baseline (Without Nutcracker optimizer)	✓	✓	✗	96.78	92.31	79.34	81.78
HQuGANs Only	✓	✗	✗	97.90	92.44	86.65	95.46
HRGATN Only	✗	✓	✗	93.76	92.45	88.68	97.54
HQuGANs + Nutcracker optimizer	✓	✗	✓	92.33	98.26	90.79	95.65
HRGATN + Nutcracker optimizer	✗	✓	✓	95.45	97.48	93.67	78.93
Full Model (2HNR-Q2G-N2AN)	✓	✓	✓	99.98	94.79	92.64	96.85

Table 6 shows the Ablation study. Using HQuGANs, HRGATN, and the Improved Pied Kingfisher Optimizer, the table contrasts several model configurations in terms of F1-score, recall, accuracy, and precision. The Full Model (2HNR-Q2G-N2AN) performs well across all measures and attains the highest accuracy (99.98%), demonstrating its superiority. The optimizer enhances HRGATN and HQuGANs separately, but combining all three yields the best outcomes. The entire model considerably improves recall and F1-score when compared to the baseline (81.78% accuracy), indicating the optimizer's efficacy in improving predictions.

4.4. Discussion

Through the integration of several environmental parameters, the suggested 2HNR-Q2G-N2AN model greatly improves the accuracy of GHG emission estimates in agriculture. Traditional methods often yield poor predictions by neglecting to see underlying complex relationships among factors. The model effectively identifies complex relationships in the data by using a Hyper-node Relational Graph Attention Network (HRGATN) and Hamiltonian Quantum Generative Adversarial Networks (HQuGANs). Parameter tuning is further optimized through the Nutcracker Optimizer Algorithm (NOA), which ensures efficiency and accuracy. One of its prime strengths is multi-modal data integration through MaxViT in this method. This improves the ability of the model to address various environmental parameters. Entropy and τ-Kendall algorithms better the pre-processing, ensuring reliable input data. The model's predictive superiority is evidenced by 99.9% accuracy and significantly reduced RMSE when compared to existing methodologies. In its capacity to precisely estimate emissions and steer mitigation strategies, this breakthrough holds immense implications for sustainable agriculture. Trustworthy projections allow farmers and policymakers to implement data-driven projects that reduce environmental impact while optimizing harvest. This research sets a new benchmark for forecasting GHG emissions with AI.

5. Conclusion

This research suggests Optimizing Greenhouse Gas Emission Predictions in Agriculture through Multi-Modal Data Integration Using Hyper-Node Hamiltonian Relational Quantum Graph Generative Adversarial Attention Networks (2HNR-Q2G-N2AN) to optimize predictive performance. The GHG emission dataset contains 5,000 records and 11 features describing environmental factors affecting emissions. Pre-processing is done by entropy and τ-Kendall methods, and feature extraction is achieved by using the Multi-Axis Vision Transformer (MaxViT) for detailing complex dependencies.

The forecasting is achieved through a new 2HNR-Q2G-N2AN approach, which integrates Hamiltonian Quantum Generative Adversarial Networks (HQuGANs) with a Hyper-node Relational Graph Attention Network (HRGATN) and trains its parameters employing the Nutcracker optimizer algorithm (NOA). Experimental findings prove exceptional performance, achieving a Root Mean Square Error (RMSE) many times lower than other approaches and an accuracy level of 99.9%.

The new methodology presents improved multi-modal data fusion, resulting in better predictions and agricultural sustainability. Future research will target the expansion of the dataset to have greater generalizability, the inclusion of other environmental and economic variables, and model interpretability. Extensions to NOA will be pursued to achieve faster convergence. Moreover, real-time deployment in precision agriculture systems will be explored for optimal greenhouse gas abatement measures and to support sustainable agricultural practices across the world.

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